Optimal Design of Multivariable Controller for Nonlinear Systems Using Variable Population Artificial Bee Colony Algorithm

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Abstract: Artificial bee colony algorithms belong to the paradigm of bio-inspired, population-based, algorithms that have been widely used to solve optimization problems. These algorithms use population of individuals/particles/bees/ants in order to explore a search space of potential solutions to a given problem and to be able to quickly converge to a global solution, or at least to a good solution. The proposed paper uses a variable population of bees in order to improve the converge rate of the algorithm, as well as a dynamic control of the inertia of the bees in order to better control the exploration of the search space. The balance between exploitation and exploration of the search space is a well-known key feature for such optimization methods and many works have been devoted to improving the management of this balance: managing population, operators, and fitness functions. To evaluate the performance of the proposed algorithm, a comparison is made with the classic artificial bee colony and genetic algorithms in tuning the multivariable the proportional-integral-derivative (PID) controllers. The proposed experimental study is the Distillation Column System (DCS) which represent control systems of complex industrial processes. Moreover, the DCS is known to be multivariable, time variant, nonlinear MIMO system with time delays. The experimental results show that the new algorithm performs better than classic approaches such as genetic algorithm and classic artificial bee colony algorithm.

Key–Words: Multivariable PID Controller, Variable Population Size, Artificial Bee Colony,Nonlinear Systems, Distillation Column System.

1 INTRODUCTION

Popularity of Proportional-Integral-Derivative (PID) controllers makes it widely used in processes and motion control system in industry because it is simple and robust in practical applications [1]. The most critical step in applications of PID controller is parameters' tuning. The parameter settings of a PID controller for optimal control of a plant depend on the plants behavior. The Ziegler-Nichols (Z-N) tuning method is perhaps the best known tuning method and experimental one that is widely used [2], but this method has some disadvantages. One of the disadvantages is necessary prior knowledge regarding a plant model. Once the controller is tuned by the Z-N method, a good but not optimum system response will be reached. The transient response can be even worse if the plant dynamics change. To assure environmental independency and good performance, the controller must be able to adapt itself to the changes of dynamic characteristics. So the control engineers are on look for automatic tuning procedures.

Today self-tuning PID digital controller provides much convenience in engineering. The tuning method includes online model-free methods. These methods tune the PID controller in loop with the given plant using an optimization algorithm such as steepest descent or Newtons method to minimize some cost function. Yet the above method cannot guarantee to find the global optimum and its calculation is also expensive. Evolutionary computation has become an important search and optimization technique for many researchers. These evolutionary computation algorithms (EA) are stochastic optimization methods that imitate biologic processes or natural phenomena [3]. Recently, new optimization techniques have been developed to satisfy the optimization requirements (i.e. speed convergence, global solution, and reduction of computing effort). There are many tuning rules for the PID parameters based on the EAs such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO)[4]-[5].

Current research activities are inspired by the behavior of bee life. Bee colony has been presented to guarantee the above requirements. It is based on the honey bee swarms and applied to solve optimization problems. Yang presented a virtual bee algorithm (VBA) to solve the numerical optimization problems [6]. Karaboga has described a bee swarm algorithm called artificial bee colony (ABC) algorithm [7], which is different from the virtual bee algorithm. In ABC, the solution candidates are modeled as food sources and their corresponding objective functions as the quality (nectar amount) of the food source. For the first step, the artificial employed bees are randomly scattered in the search domain producing initial solutions. The initial solution represents the number of employed or onlooker bees which are considered equal until the end of the algorithm. However like most of the population based algorithms, ABC also has some non-appreciable drawbacks. One of the most important points is the impact of the initial population distribution which has affected the overall performance of artificial bee colony (i.e. the global solution, the convergence rate, and explorations for the global solution). However, the performance of an algorithm depends on both exploration and exploitation phases for a required feasible solution. More recent, new modifications have been applied on the standard artificial bee colony such as one-position inheritance ABC,dynamic inertia weight ABC, and weighted sum ABC [8] -[10],respectively.

In this paper, a variable population size artificial bee colony (VPS-ABC) based on global best with periodical reinitialization strategy is proposed that follows a saw-tooth scheme with a specific amplitude and period of population variation. This algorithm differs from the above techniques by using variable food sources for both employed and onlookers bees with global best guiding strategy instead of using fixed size food sources without guiding strategy. The main idea of VPS-ABC is to divide the time generations into periods (T). In each period the number of food sources starts with an initial number then decreases gradually. At the beginning of the next period randomly generated individuals around the global food source reinstall the previous population. In each population period new energetic food source individuals around the global solution start the race to search the neighborhood for the global best particles, resulting in more exploration of the search space and increasing the diversity of the population by incorporating dynamic initial weight in the basic equation of the food sources generation. ABC is able to escape from the local optima. Moreover, the overall performance is improved and the computation time is reduced. To show the fitness of the proposed algorithm; the new developed algorithm is carried out for the optimal tuning of multivariable PID controller to the Distillation Column System (DCS) which is a 2x2 MIMO system with strong interactions between inputs and outputs containing non negligible time-delays. The experimental results proof that VPS-ABC based on global best reinitialization strategy outperforms the results obtained by the Decentralized Relay Feedback (DRF) controllers [11].

The rest of the paper is organized as follows. In section II, the basic concepts and the most common variants of ABC are explained. Section III describes VPS-ABC and the global best reinitialization strategy is presented in details. An overview of evolutionary PID controllers and performance indices used for both single and multivariable case are presented in section IV. In section V, results and comparison among VPS-ABC, classical ABC, GA, and DRF in case of DCS are presented. Finally, concluding remarks appear in section VI.

2 ARTIFICIAL BEE COLONY

An intelligent behavior of honey bee colony which search new food sources around their hive was considered to compose bee colony algorithm. There are several models based on honeybees. This model was initially proposed by Karaboga [7] and then lately formally introduced by Basturk and Karaboga [12]. ABC belongs to the group of algorithm which simulates foraging behavior of haney bees.

2.1 Foraging Model

Tereshko developed a model of foraging behavior of a honeybee colony based on reaction–diffusion equations [13]-[14]. This model that leads to the emergence of collective intelligence of honeybee swarms consists of three essential components: food sources, employed foragers, and unemployed foragers. It defines two leading modes of the honeybee colony behavior: recruitment to a food source and abandonment of a source. In ABC algorithm, the colony of artificial bees consists of three groups of bees called employed bees, onlookers, and scouts. While half of the colony consists of the employed artificial bees, the other half includes the onlookers. There is only one employed bee for every food source. That is, the number of employed bees is equal to the number of food sources around the hive. ABC algorithm has been applied successfully to a large number of various optimization problems [15]-c6. In each cycle, food sources are mutated with their neighbors to produce new solutions and then evaluated based on the fitness function. A food source that does not produce improvement in solutions is assumed abandoned source.

2.2 ABC phases

In the ABC algorithm, each cycle of the search consists of three phases:

1. *Employed Bee Phase:* In this phase, ABC sends employed bees onto the food sources and then measures the source quality (i.e. quantity, richness, and closeness,...etc.). Employed bees carry this information to the hive and then throughout the dancing area (area of information exchange) share it with the onlookers. Employed bee memorizes its food source and then may be continue in the same food source or select a new one. An artificial bee produces a new solution with formula [7].

$$v_{i,j} = x_{i,j} + \Phi_{ij}(x_{i,j} - x_{k,j}) \qquad (1)$$

$v_{i,j}$ is a new solution that comes from food source $x_{i,j}$ and its neighbor $x_{k,j}$, where i and k are two random indices, Φ is randomly produced number in range [-1,1].

2. *Onlooker Bee Phase:* Onlookers decide and select the source food depending on the nectar information. The probability of selecting certain source food increases

as the information received from the dancing area mean large amount of nectar exists with high quality. Onlookers choose a food source with a probability calculated using different schemes. In this work an artificial onlooker bee chooses a food source with probability p_i expressed as

$$p_i = a\frac{fit_i}{\sum_i^k fit} + b \quad (2)$$

Where a and b are two arbitrary numbers in range [0, 1], fit_i is the fitness value of solution i, and k is the number of employed bees. Basturk and Karaboga [16], has expressed the fitness function as

$$fit_i = \begin{cases} \frac{1}{1+F_i}, & \text{if} \quad F_i \geq 0 \\ 1 + abs(F_i), & \text{if} \quad F_i < 0 \end{cases} \quad (3)$$

Where F_i is the objective function to be optimized.

3. *Scout Phase:* When an employed bee deices to leave its food source, it becomes a scout. In ABC, if a food source position cannot be improved further through a predetermined number of cycles, then that food source is discarded. The value of predetermined number of cycles is an important control parameter of the ABC algorithm, which is called *limit* for abandonment. Moreover, the number of scouts is limited by the colony size and dimension of the problem.

3 Variable Population Size Artificial Bee Colony

In ABC, the system is initialized with a population of random solutions and searches for the optima by updating the population in the succeeding generations. However, reaching the global solution and faster convergence rate are the two basic advantages in any optimization algorithm; so that improving the convergence rate and the computational effort is the motivation to this work:

3.1 Variable Population Size

Varying the population size in the proposed algorithm depends on reducing, periodically, the number of the food sources available for both employed bees and onlooker bees phase for a population period time T. The period time T is suggested to energize the available food sources in each period by using reinitialization strategy. This modification is promising, because the most evolutionary algorithms (i.e. ABC, GA, PSO...) suffer from the impact of the initial population on the new produced solution, which reflect the difficulty to reach the global solution and settled to a local one. Moreover, VPS-ABC algorithm starts with a bigger food sources at the beginning which provides a better initial signal for the ABC evolution process and guides the algorithm to the region of global solution; whereas, a smaller population size is adequate at the end of the run, where the ABC converges to the optimum [17]. The proposed food source number profile is suggested to decrease linearly with the generation time as depicted in the following figure:

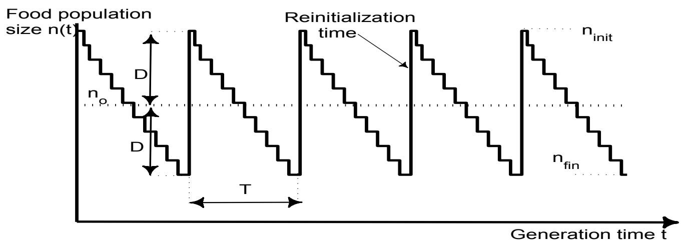

Figure 1: The size of food sources

In Fig.1, the number of food sources starts with maximum number n_{init} and linearly decreases to n_{fin}. The average number of population size is n_o where $n_{init} \leq n_o \leq n_{fin}$ for a population period time T. This process is then repeated along the generation time. The suggested function that produces the food source number is introduced by [18] to generate the population size in (Saw-Tooth GA) scheme as follow:

$$n(t) = int(n_o + D - \frac{2D}{T-1}[t - T * int(\frac{t-1}{T}) - 1]) \quad (4)$$

where T is the population period time, t the generation time, D the maximum deviation around the average population size (i.e. $n_o - D \leq n(t) \leq n_o + D$),$int$ refers to $integer$. If $D = 0$, VPS-ABC returns to constant food source artificial bee colony algorithm.

3.2 Reinitialization Strategy

The effect of population reinitialization is in a sense similar to the mutation operator in Genetic Algorithms. Such operator introduces random changes in the population to increase diversity in the suggested population space and achieve better exploration of the search space. This effect is favorable when the GA population prematurely converges to a certain point or local optimum and further improvement is not likely. Therefore, population reinitialization represents a good strategy especially for the case of multimodal problems[18]. In this work, the global best reinitialization strategy is introduced to improve the overall performance of the standard ABC. This strategy is based on guiding the bees around the most recent best food source to reach the best food source; this variant is inspired from the particle swarm optimization algorithm. The global best reinitialization strategy is executed at the end of the population period time T as shown in Fig.1. This strategy helps the ABC algorithm to redistribute the expected solutions around the region of the global minimum in each population period time T which have a good impact on the convergence rate and the overall performance of (ABC). The reinitialization equation is proposed to be:

$$v_{i,j} = x_{i,j} + \Phi_{ij}(x_{global} - x_{i,j}) \quad (5)$$

$v_{i,j}$ is a new solution comes from food source $x_{i,j}$ around x_{global} the global best food source found position among all food sources, Φ is a randomly produced number in range [0,1].

3.3 Dynamic Inertia Weight

It was shown in [19] that, introducing dynamic inertia weight parameter in the basic ABC equation (1) can play a good role in controlling the impact of the previous foods on the new expected one as follow:

$$v_{i,j} = w_i x_{i,j} + \Phi_{ij}(x_{i,j} - x_{k,j}) \quad (6)$$

The inertia weight w_i is employed to manipulate the impact of the previous history of velocities on the current velocity. Therefore, w_i resolves the tradeoffs between the global (wide ranging) and local (nearby) exploration ability of the swarm [19]. A large inertia weight encourages global exploration (moving to previously not encountered areas of the search space), while a small one promotes local exploration, i.e., fine-tuning the current search area. A suitable value for w_i provides the desired balance between the global and local exploration ability of the swarm and, consequently, improves the effectiveness of the algorithm[9][19]. A linearly-increasing time-dependent inertia weight is implemented according to the following updated equation:

$$w_i = (w_{init} - w_{fin})(\frac{N-i}{N}) + w_{fin} \quad (7)$$

Where w_{init}= initial inertia weight, w_{fin} = final inertia weight, N = maximum iteration value and i= variable iteration index. Note here that the inertia weight w plays an important role in the convergence of the ABC algorithm to the global optimal solution and hence has an influence on the time taken for a simulation run. The following flow chart illustrates the function of the PID based VPS-ABC:

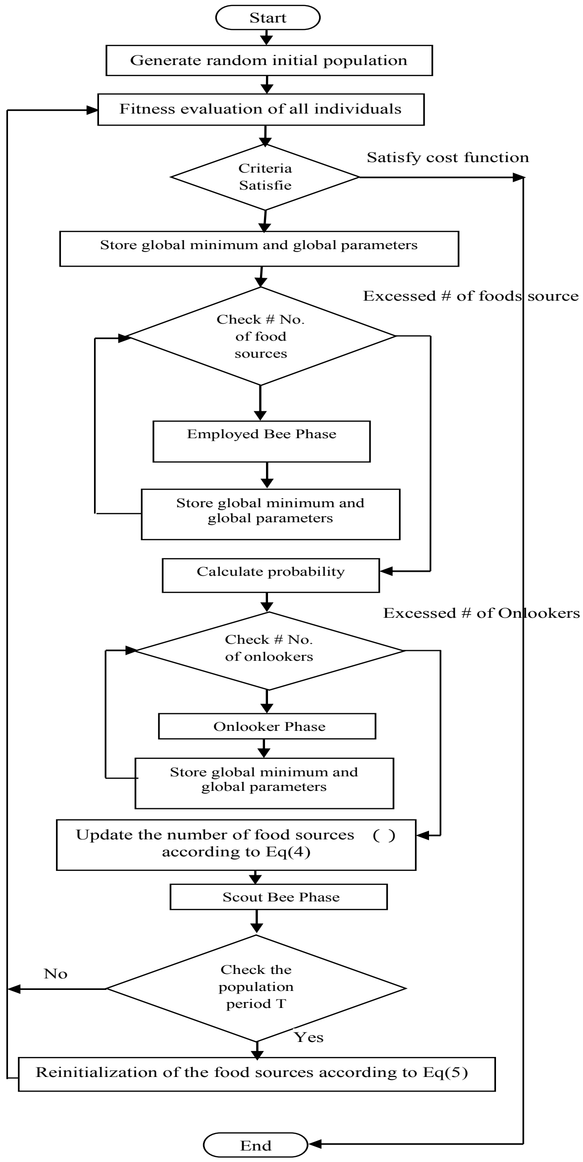

Figure 2: Flow chart of variable population size artificial bee colony algorithm

4 Evolutionary PID Controller

In designing PID controllers, the goal is to tune proper coefficients K_P, K_I and K_D so that the output has some desired characteristics. Usually in time domain, these characteristics are given in terms of overshoot, rise time, settling time and steady state error.

4.1 Multivariable PID controller design

Many systems encountered in practice consist of several interconnected loops. Classical MIMO techniques usually solve the controller design problem successfully. Their drawback consists mainly in the fact that the results are state-space high-order controllers. Moreover, systems containing non negligible time-delays cannot be handle by such procedures. Considerable attention has been given to the use of SISO procedures for the tuning of decentralized PID controllers for MIMO systems due to the fact that many systems can be made diagonally dominant (i.e. interactions between loops are not predominant) by designing appropriated decoupling compensators[11]. Donghai et al.[20] has present an optimization method of tuning decentralized PI/PID controllers based on genetic algorithms.

Consider the multivariable PID control loop in Fig.3,where the multivariable process $P(s)$ could be demonstrated as follows:

$$\text{P(s)} = \begin{bmatrix} p_{11}(s) & \cdots & p_{1n}(s) \\ \vdots & \ddots & \vdots \\ p_{n1}(s) & \cdots & p_{nn}(s) \end{bmatrix} \quad (8)$$

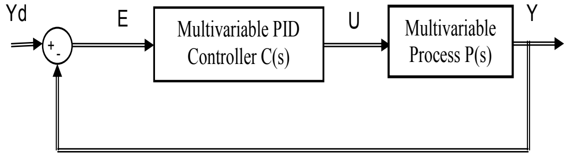

Figure 3: Block diagram of multivariable controlled process

where $p_{ij}(s)$ is the transfers function between y_i and u_j. In Fig.3,vectors Y_d,Y,U,and E are in following form:

$$Y_d = \begin{bmatrix} y_{d1} & y_{d2} & \cdots & y_{dn} \end{bmatrix}^T \tag{9}$$

$$Y = \begin{bmatrix} y_1 & y_2 & \cdots & y_n \end{bmatrix}^T \tag{10}$$

$$U = \begin{bmatrix} u_1 & u_2 & \cdots & u_n \end{bmatrix}^T \tag{11}$$

$$E = Y_d - Y = \begin{bmatrix} e_{11} & e_{22} & \cdots & e_{nn} \end{bmatrix}^T \tag{12}$$

Multivariable PID controller $C(s)$ in Fig.3, is in the following form:

$$\text{C(s)} = \begin{bmatrix} C_{11}(s) & \cdots & C_{1n}(s) \\ \vdots & \ddots & \vdots \\ C_{n1}(s) & \cdots & C_{nn}(s) \end{bmatrix} \tag{13}$$

where C_{ij} that $ij \in [1, 2, ..., n]$ is as follows

$$C_{ij}(s) = K_{P_{ij}} + K_{I_{ij}} \frac{1}{s} + K_{D_{ij}} \tag{14}$$

where $K_{P_{ij}}$is the proportional,$K_{I_{ij}}$ is the integral and $K_{D_{ij}}$ is the derivative gains of the PID controller $C_{ij}(s)$.

4.2 PID preformance indices

The most common performance indices have been suggested to measure the performance of the optimum PID controller are the integral absolute error (IAE), the integral square error(ISE), the integral time absolute error (ITAE), and the integral time square error (ITSE). These indices are normally calculated based on the step response.

1. *Integral Absolute Error (IAE)*

$$I_{IAE} = \int_0^\infty |r(t) - y(t)|dt = \int_0^\infty |e(t)|dt \tag{15}$$

2. *Integral Time Absolute Error (ITAE)*

$$I_{ITAE} = \int_0^\infty |te(t)|dt \tag{16}$$

3. *Integral Square Error (ISE)*

$$I_{ISE} = \int_0^\infty e^2(t)dt \tag{17}$$

4. *Integral Time Square Error (ITSE)*

$$I_{ITSE} = \int_0^\infty te^2(t)dt \tag{18}$$

The transient response parameters such as, maximum overshot (M_p), settling time (T_s), rise time (T_r) are normally considered significant where the benefits of faster systems necessitates minimum possible values for them [16].

In designing of a multivariable controller, one of the major aims is diagonal domination of the control process [11]. That is the controller is to be designed in such a way that $y_i(t)$ is able to track the desired input $y_{di}(t)$ and to reject the response of other inputs $y_{dj}(t)$, for i,$j \in \{1, 2, ..., n | i \neq j\}$.
Considering the decoupling aim (ISE) is defined in the following form:

$$\textit{ISE} = \sum_{i=1}^{n}\sum_{j=1}^{n} ISE_{ij} = \sum_{i=1}^{n}\sum_{j=1}^{n} \int_0^\infty e_{ij}^2(t)dt \tag{19}$$

The ISE squares the error to remove negative error components.

5 Simulations

Application of the proposed VPS-ABC algorithm to a real problem has proven its capability to deal with difficult optimization problems. In this work, a multivariable PID controller is designed for a MIMO chemical system. Comparison experiments have been carried out to evaluate the performance of the proposed algorithm, VPS-ABC algorithm is compared with GA algorithm in tuning the multivariable PID controllers.

5.1 Distillation Column System (DCS)

DCS system is a typical 2×2 model [11] with strong interactions between inputs and outputs. The four transfer functions processes have first-order dynamics and significant time delays. A simple schematic of distillation column system is shown in Fig.4.

The matrix transfer function of DCS [11] is defined as:

$$\begin{bmatrix} X_D(s) \\ X_B(s) \end{bmatrix} = \begin{bmatrix} \frac{12.8e^{-s}}{(1+16.7s)} & \frac{-18.9e^{-3s}}{(1+21s)} \\ \frac{6.6e^{-7s}}{(1+10.9s)} & \frac{19.4e^{-3s}}{(1+14.4s)} \end{bmatrix} \begin{bmatrix} R(s) \\ S(s) \end{bmatrix} \tag{20}$$

where $X_D(s)$and $X_B(s)$ are percentage of methanol in the distillate and percentage of methanol in the bottom products, respectively. Also $R(s)$ and $S(s)$ are reflux flow rate and steam flow rate in the boiler, respectively.

The control objectives are:

- tracking the control inputs $R(s)$ and $S(s)$ by the outputs $X_D(s)$ and $X_B(s)$.

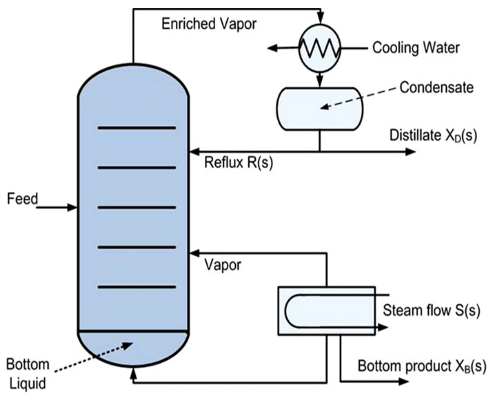

Figure 4: Schematic diagram of the Distillation Column Systems(DCS)

- diagonally domination of the controlled process as much as possible.

In [11] a multivariable PID controller for DCS is designed using decentralized relay feedback (DRF) method. The diagonal and off-diagonal elements of this controller are designed in PI and PID forms, respectively. To compare the results of VPS-ABC with DRF method in tuning parameters of the PID controller for the DCS.

C(s) is considered to take the following form:

$$C(s)=\begin{bmatrix} K_{P_{11}}+\frac{K_{I_{11}}}{s} & K_{P_{12}}+\frac{K_{I_{12}}}{s}+K_{D_{12}}s \\ K_{P_{21}}+\frac{K_{I_{21}}}{s}+K_{D_{21}}s & K_{P_{22}}+\frac{K_{I_{22}}}{s} \end{bmatrix} \tag{21}$$

So the objective will be a 10 dimensional optimization problem of determining the optimal coefficients: $[K_{P_{11}}K_{I_{11}}K_{P_{12}}K_{I_{12}}K_{D_{12}}K_{P_{21}}K_{I_{21}}K_{D_{21}}K_{P_{22}}K_{I_{22}}]$

5.2 Settings

A VPS-ABC algorithm with population period $T = 10$ and initial food sources $n_{init} = 15$ and final food sources $n_{fin} = 5$ with mean population size $n_o = 10$ is used in order to tune the multivariable controller parameters(25). ABC algorithm limit equal 10 (food source which could not be improved through "limit" trials is abandoned by its employed bee)[12]. Constants of probability equation (2) are chosen $a = 0.75$ and $b = 0.25$. The dynamic range of the inertia weight [0.6, 1] where $w_{init} = 0.6$, and $w_{fin} = 1$. The maximum iterations of the VPS-ABC are set to 100. For GA, the population size of 20, mutation rate 20% and with other default parameters. Any set of PID parameters that gave unstable system performance had their weighted error value set really high so that they would not be chosen for selection in the ABC learning process.

5.3 Results

The tuning of VPS-ABC based PID controller's results will be compared to those obtained from the GA technique. Moreover, The obtained results based on minimizing ISE (19) are compared with the results obtained by the PID-controller designed by DRF[11]. Several pre-experiments are conducted to determine the parameters settings for VPS-ABC, GA,and DRF algorithms that yield the best performance. The following table gives a comparative study between the different techniques with respect to the optimal PID parameters.

Table 1: Optimized PID Gains Corresponding VPS-ABC,GA and DRF

$Parameter$	$VPS-ABC$	GA	DRF
$k_{p_{11}}$	0.2000	0.26697	0.184
$k_{i_{11}}$	0.0469	0.027581	0.0467
$k_{p_{12}}$	-0.0258	-0.044637	-0.0102
$k_{i_{12}}$	-0.0314	-0.044239	-0.0229
$k_{d_{12}}$	-0.0486	-0.065873	0.00824
$k_{p_{21}}$	-0.0597	-0.027727	-0.0674
$k_{i_{21}}$	0.0178	0.0073777	0.0159
$k_{d_{21}}$	-0.1537	-0.22793	-0.0536
$k_{p_{22}}$	-0.1095	-0.15116	-0.066
$k_{i_{22}}$	-0.0168	-0.023364	-0.0155

So, the optmial VPS-ABC based multivariable PID controller C(s) will take the following form:

$$C(s)=\begin{bmatrix} 0.2+\frac{0.0469}{s} & -0.0258-\frac{0.0314}{s}-0.0486s \\ -0.0597+\frac{0.0178}{s}-0.1537s & -0.1095-\frac{0.0168}{s} \end{bmatrix} \tag{22}$$

In [11], the suggested multivariable PID controller by DRF method was as follows:

$$C(s)=\begin{bmatrix} 0.184+\frac{0.0467}{s} & -0.0102-\frac{0.0229}{s}+0.0082s \\ -0.0674+\frac{0.0159}{s}+0.0536s & -0.066-\frac{0.0155}{s} \end{bmatrix} \tag{23}$$

Simulation results comparing between the three techniques VPS-ABC, GA, and DRF are carried out. The ISE cost function (19) has been used to dominate the diagonal elements of DCS system. Fig.5 depicts the four transfer functions step response of DCS system under optimization of the decoupling aim (19). Moreover,the response of the DCS system having optimal PID controller (22) due to square wave input is depicted in Fig.6.

It is seen from Fig.5 and table II, the proposed controller (22) dominates the diagonal outputs and rejects the outputs of other inputs where $ISE_{12} = 0.4132$ and $ISE_{21} = 0.0912$ are very small values. Moreover, the proposed controller can track the control inputs by the outputs when applying square wave input as shown in Fig.6.

Results clearly demonstrate that the VPS-ABC algorithm have outperformed the method proposed by[15] and GA algorithm in designing a multivariable PID controller for DCS system.

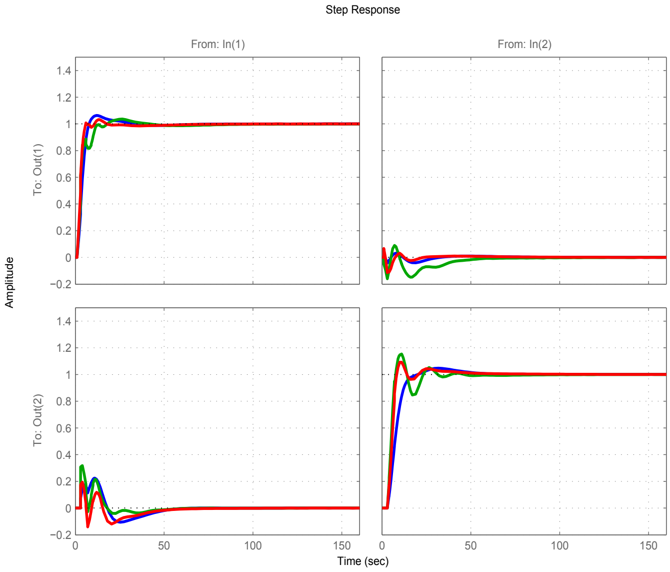

Figure 5: Step response of DCS system having optimal PID under optimization of ISE (19)

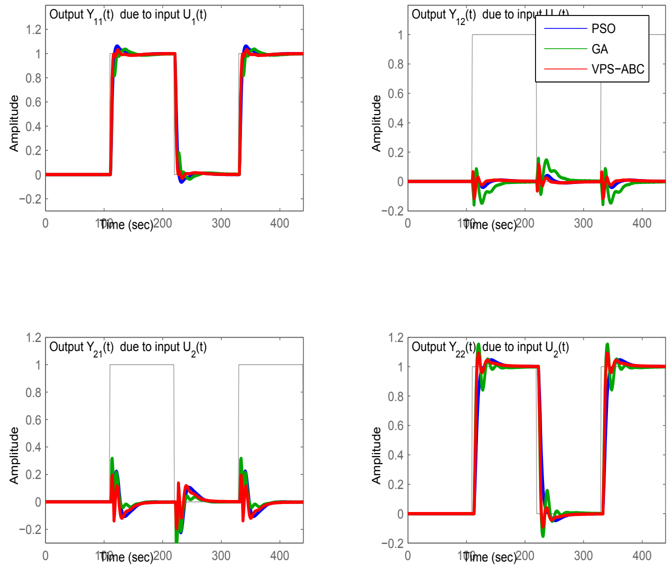

Figure 6: Distillation Column System (DCS) response due to square wave input

Table 2: Different parts of ISE Corresponding VPS-ABC,GA and DRF

$Parameter$	$VPS-ABC$	GA	DRF
ISE_{11}	6.1022	6.9284	7.6634
ISE_{12}	0.413	1.0674	1.0193
ISE_{21}	0.0912	0.4384	0.0276
ISE_{22}	12.2682	12.0561	15.4640
$Cost$	18.8748	20.4904	24.1744

6 CONCLUSION

Improving the performance of the standard ABC algorithm by controlling the effect of the initial population in the new expected solution, and reducing the computational effort are very interesting problems in EAs. In this paper, a novel variable population size artificial bee colony with global best reinitiatlization strategy algorithm has been presented. The main idea in VPS-ABC depends on reducing the number of food sources gradually for a period of time then guiding the employed and onlooker's bees around the global best. This mechanism is repeated along the time generation. The VPS-ABC strategy has been proposed to overcome the impact of the initial population, reduce the computational effort, and help the algorithm to explore the global solution quickly. The proposed algorithm improves the convergence rate of the standard ABC and the results show that the proposed strategy is highly competitive, outperforming the standard ABC. Comparison experiments have been carried out for optimal tuning of multivariable PID-controller to DCS which is a 2×2 MIMO system with time delays and strong interactions between inputs and output. The time response characteristics of the processes demonstrate the superiority of VPS-ABC based on global best reinitialization strategy comparing to the other algorithms.

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